Cognition based Service Selection in Semantic Web Service Composition

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Abstract- Selecting most appropriate service among the available services for performing an activity is one of the important activities of semantic web service composition process. The paper presents a cognitive parameters based model for rating the different service providers based on their cognitive parameters like trustworthiness, capability, commitment, intention, desire, reputation etc. The model covers a wide range of parameters in its rating and provides a feedback system which will affect the reputation of selected service provider.

Keywords: cognition, semantic web, service, service composition, service selection.

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1. Introduction

Out of the various aspects of Semantic Web Service (SWS) composition process like automatic discovery, selection, and composition, the selection of most appropriate semantic web service can be considered as one of the most important. Various cognitive parameters like capability, desire, intention, commitment, trust, reputation etc. can prove to be deciding factors in semantic web service selection and composition. They can be used to decide the finally one SWS to invoke by the user out of the discovered services. The presented Cognitive Parameters Based Selection Model (CPBSM) can be easily integrated with the multi-agent based SWS composition process. CPBSM can be used by any requester agent for rating provider agents based on their past performance, trustworthiness, and reputation. So, it can be used by the requester agent for the selection of best performing provider agent.

To our knowledge, this issue of selection based on cognitive parameters has not been thoroughly addressed in the literature till now, due to the lack of formal measurement of cognitive parameters. However the work by [3] has presented a method for selection of service provider agents based on some cognitive parameters. But the agent selection model in [3] only considers capability and credibility assessment as the base for agent selection and then performs negotiation with each of the capable agent. But assessing these parameters only, may not result into the selection of best performing agent. Among a large number of novelty features in the presented model, some of them are: providing the novel formalization of cognitive parameters, categorizing the input request based on values of some parameters and then providing consideration to it in service provider selection, providing a novel method of measuring the reputation of agent, providing a dynamic feedback system affecting the reputation of selected service provider based on quality of its present service.

The paper has been structured as follow. Apart from introduction in section-1, section-2 presents detailed description of proposed cognition based selection model. Section-3 deals with implementation issues and applying the proposed model for education planning problem and the paper has been concluded in section-4 with some discussion on future work.

2. Cognitive based Selection Model

Cognitive parameters such as reputation, trust, capability, desire, intention etc. can play an important role in semantic web service selection and composition. The one SWS, which will be finally invoked by the user out of discovered SWSs, can be chosen based on its cognitive parameters. The presented Cognitive Parameters Based Selection Model (CPBSM) can be easily integrated with the Multi-Agent System (MAS) based SWS composition process. CPBSM can be used by any service requester agent (SRA) for rating service provider agents (SPA) based on their past performance, trustworthiness, and reputation. CPBSM calculates an Index of Selection (IoS) for the agent based on its trustworthiness and reputation among the requester agents. IoS calculated can be, then, used as base of selection for best provider agent. Where, requester agent is any agent which wants to take any type of services from other agent, called provider agent. However, the services can be of coordinating a task or performing a specific task or any other similar activities. So, the IoS can be defined as the weighted sum of trustworthiness and reputation of agent.

$$IoS = \alpha(TI) + (1-\alpha)(RI) \quad , \qquad \ldots(1)$$
$$Where \quad 0 \le TI \le 1, \quad 0 \le RI \le 1, \quad 0 \le \alpha \le 1, \quad 0 \le IoS \le 1$$

Where, TI is the Trust Index, representing a value which is measure of the trustworthiness of the agent and RI is the Reputation Index, representing a value which is measure of the reputation of the agent among other similar requester agents and the given requester agent. α is the measure of relative weight given to trustworthiness as compared to reputation of agent in its selection. The calculation for TI and RI is as shown in next sections. As RI also include the reputation value from the present requester agent, so IoS is not only considering its trustworthiness and reputation among other fellow similar requester agents, but also the reputation of reference agent in view of present requester. This model also uses the concept of categorizing the input requested task based on its parameters into n task-type categories T_1, T_2 … T_n and provides consideration to these categories into IoS calculation. For example, for travel booking scenario, the categorization can be based on the expertise in dealing particular continents flights, price-range etc.

2.1 Measuring Trustworthiness of Agent

The trust of an agent on other information source agent is defined as the confidence in the ability and intention of an information source to deliver correct information [1]. We have adapted this definition for the multi-agent based SWS composition system, to define the trust of SRA on the SPA as the confidence in the ability and intention of the SPA to deliver the committed services. So TI can be defined as:

$$TI = CI * \quad II \qquad ,$$
$$Where\, 0 \le CI \le 1, \quad 0 \le II \le 1 \qquad \ldots(2)$$

Where, CI is the Capability Index, representing a value which is measure of the capability of the agent and II is the Intention Index, representing a value which is measure of the intention of the agent to deliver committed service.

Capability of an agent is the ability to react rationally towards achieving a particular goal. An agent can only perform for its committed goal, if it has capability to do so [7]. It is the measure of both capacity and expertise of agent. So, capability of an agent can be judged from its past performance towards the accepted tasks and with how much perfection these were performed. So, CI of an agent can be calculated as follow:

Observe that the performance of an agent may vary depending on the type of task or problem it is handling. So, it will show different capability with different task-type. So, we have considered that a task which is handled by an agent can be categorized into n task-types. Also the capability of an agent can not be considered to be only binary i.e. Task Performed or Task Not Performed. But, we have considered following multiple scenarios while judging the capability of agent:

(i) Task Completed successfully within the committed parameters.
(ii) Task Completed successfully but with some relaxed parameters like may not be within the committed time (but acceptable one), with more price, with less quality, with less quantity etc.
(iii) Task Not Completed.

The first scenario shows the good capability of agent, while second shows some less capability as compared to first. But the last one shows the inability of agent and will negatively affect the overall capability. So, each scenario will effect differently on the capability measure of agent. These scenarios also show perfection level of agent. So, with following parameters the capability index (CI_k) of an agent for a task-type T_k can be given by equation (3).

Let CI_1, CI_2 … CI_n be the capability indexes of agents for task-types T_1, T_2 … T_n respectively. $N_C^k, N_{CR}^k, \quad N_{NC}^k$ be the number of tasks completed successfully with committed parameters, completed successfully with relaxed parameters and not completed respectively out of total N^k tasks of task-type T_k, where k = 1, 2 … n. These parameters can be maintained in the ontological service profiles of agents. WC_C, WC_{CR}, WC_{NC} be the capability weights given to the tasks completed successfully, completed successfully but with relaxed parameters, and not completed respectively. Then CI_k can be given as:

$$CI_k = \frac{WC_C * N_C^k + \quad WC_{CR} * N_{CR}^k \quad - \quad WC_{NC} * N_{NC}^k}{(WC_C + WC_{CR} + WC_{NC}) * N^k} \qquad \ldots(3)$$

And following relations should hold:

1. $N^k = N_C^k + N_{CR}^k + N_{NC}^k$
2. $N^1 = N^2 = \ldots = N^n = 100$, as equation (3) will take percentage values for $N_C^k, N_{CR}^k, \quad N_{NC}^k$ out of total N^k tasks.

3. $0 \le CI_k \le 1$, as equation (3) has value normalized by $(WC_C + WC_{CR} + WC_{NC}) * N^k$.

4. $WC_C > WC_{CR}$, This will cause greater weight, in the capability calculation, to the task which is completed successfully within committed parameters than the tasks completed successfully but with relaxed parameters.

5. $WC_{NC} > WC_C$, As is clear from equation (3) that W_{NC} is causing the negative effect on the capability of agent, but this relation will cause an extra penalty over the agent for not completing the accepted task.

6. Values of WC_C, WC_{CR}, WC_{NC} can be taken under any fixed range, but for uniformity, we can take it between 0 and 1.

Now, it is to be noted that from the view of SRA, all the task-types can not be given equal weight. Some task-types may be difficult to perform than the other ones. So, Overall CI will be the weighted mean of individual capability indexes for each task-type. If WD_1, WD_2 … WD_n be the difficulty weights (their value can be in any fixed range, but for uniformity, we can take it between 0 and 1) for task-types T_1, T_2 … T_n respectively, then overall CI of agent can be given by the weighted arithmetic mean of capability indexes of agent for all task-types:

$$CI = \frac{\sum_{i=1}^{n} CI_i * WD_i}{\sum_{i=1}^{n} WD_i} \quad \text{Where } 0 \le CI \le 1 \quad \ldots (4)$$

Intention of an agent tells about the set of plan for the goal it has committed to achieve. [11] has defined intention as "Intention is desire with commitment" and [2] has explained intention as "Intention is choice with commitment". So, intention can be defined as the combination of desire and commitment, where desire tells about the internal mental state of the agent, while the commitment tells about the external public state of agent which even can be written beforehand as an agreement or contract. So, the II of an agent can be calculated as:

$$II = DI \quad * \quad CommI \,,$$
$$Where\ 0 \le DI \le 1, \quad 0 \le CommI \le 1 \qquad \ldots (5)$$

Where, DI is the Desire Index, representing a value which is measure of the performance of the agent for its desired tasks and CommI is the Commitment Index, representing a value which is measure of the commitment of the agent towards accepted work.

Desire of an agent determines its motivation what it is trying to bring about. It defines the state-of-the-art that needs to be accomplished. It differs from the intention in the point that, desire defines the motivation towards the work, while intention may be seen as agent's immediate commitment in implementing an action, as is also clear from equation (5) [8]. So, if an agent has desire for a task, then ideally it should perform well for that task. So, measuring the past-performance of agent for the tasks presently desired by it, can be good measure of its honesty towards its desire. And from it, SRA can properly judge, how it will react for its present desires. So, we have incorporated a parameter, Performance-to-Desire (PD), which can be defined as the measure of the performance of an agent for the tasks for which it has shown desire. We will consider this concept of desire for different task-types. Now, if an agent has published its profile for a task of particular domain (like trip planning), then it is obvious that it is desirous of doing tasks of that domain, but may not be of all types. Also, the desired task-types of agent may vary with time. So, the list of desired tasks has to be checked by SRA for each request. This information can be maintained in the published profile of the SPA. Now, let at the time of request, the desire-list of task-types for SPA is $(DT_1, DT_2 \ldots DT_d)$, where $(DT_1, DT_2 \ldots DT_d) \subseteq (T_1, T_2 \ldots T_n)$ and T_r be the task-type of input requested task. Then, the DI of agent can be calculated as the combination of PD of agent for $(DT_1, DT_2 \ldots DT_d)$ and PD for T_r. It must be noted that, IoS for this reference SPA will be calculated only if $T_r \in (DT_1, DT_2 \ldots DT_d)$. So, using the concepts as described in the calculation of CI, the PD_k for desired task-type DT_k can be calculated as below:

Let PD_1, PD_2 … PD_d be the Performance-to-Desire of agent for task-types DT_1, DT_2 … DT_d respectively. ND_C^k, ND_{CR}^k, ND_{NC}^k be the number of tasks completed successfully with committed parameters, completed successfully with relaxed parameters and not completed respectively, out of total ND^k tasks of task-type DT_k, where k = 1, 2 … d. These parameters can be maintained in the ontological service profiles of agents. WDs_C, WDs_{CR}, WDs_{NC} be the performance-to-desire weights given to the tasks completed successfully, completed successfully but with relaxed parameters, and not completed respectively for the tasks which are presently desired by agent. Then PD_k can be given as:

$$PD_k = \frac{WDs_C * ND_C^k + WDs_{CR} * ND_{CR}^k - WDs_{NC} * ND_{NC}^k}{(WDs_C + WDs_{CR} + WDs_{NC}) * ND^k} \qquad \ldots (6)$$

And following relations should hold:

1. $ND^k = ND_C^k + ND_{CR}^k + ND_{NC}^k$

2. $ND^1 = ND^2 = \ldots = ND^d = 100$, as equation (6) will take percentage values for $ND_C^k, ND_{CR}^k, \quad ND_{NC}^k$, out of total ND^k tasks.

3. $0 \le PD_k \le 1$, as equation (6) has value normalized by $(WDs_C + WDs_{CR} + WDs_{NC}) * ND^k$.

4. $WDs_C > WDs_{CR}$, This will cause greater weight in the PD calculation to the task which is completed successfully within committed parameters than the tasks completed successfully but with relaxed parameters.

5. $WDs_{NC} > WDs_C$, As is clear from equation (6) that W_{NC} is causing the negative effect on the PD of agent, but this relation will cause an extra penalty over the agent for not completing the accepted task.

6. Values of WDs_C, WDs_{CR}, WDs_{NC} can be taken under any fixed range, but for uniformity, we can take it between 0 and 1.

7. $WDs_C = WC_C, WDs_{CR} < WC_{CR}, WDs_{NC} > WC_{NC}$, this will work as extra penalty for not performing the task within parameters and not completing task, even though agent shows the desire for it.

As in the case of CI calculation, all desired task-types can not be given equal weight in judging the PD of agent. So, overall PD will be the weighted mean of individual Performance-to-Desire values for each desired task types. If $WDsD_1$, $WDsD_2$ … $WDsD_d$ be the difficulty weights (their value can be in any fixed range, but for uniformity, we can take it between 0 and 1) for task-types DT_1, DT_2 … DT_d respectively, then overall PD of agent can be given by the weighted arithmetic mean of Performance-to Desire values of agent for all task-types:

$$PD = \frac{\sum_{i=1}^{n} PD_i * WDsD_i}{\sum_{i=1}^{n} WDsD_i}$$

Where $0 \le PD \le 1$ $\quad \ldots(7)$

Now, if PD_r be the Performance-to-Desire for requested task type T_r, which can be calculated using equation (6), then the DI of agent should hold:

$$DI \propto PD \text{ and } DI \propto PD_r$$

So, DI will be:

$$DI = PD * PD_r \quad \ldots(8)$$

Commitment of an agent implies some temporal persistence of the intention. The commitment of an agent leads it to make plans for its action based on its intention. It is a conduct-controlling characteristic of agent, which says that if an agent is committed to do something, then it should not consider the actions which are incompatible with so doing [11]. So, commitment of an agent can be judged from the point that how much of its past actions were compatible with its commitments and how much were incompatible. Hence, the $CommI_k$ of an agent for task-type T_k can be given as:

$$CommI_k = \frac{WCm_C * N_C^k - WCm_{CR} * N_{CR}^k - WCm_{NC} * N_{NC}^k}{(WCm_C + WCm_{CR} + WCm_{NC}) * N^k} \quad \ldots(9)$$

Where, $CommI_1$, $CommI_2$ … $CommI_n$ be the Commitment Indexes of agent for task-types T_1, T_2 … T_n respectively. WCm_C, WCm_{CR}, WCm_{NC} be the commitment weights given to the tasks completed successfully, completed successfully but with relaxed parameters, and not completed respectively for the task which has been committed by agent. In addition to the relations shown in calculation of CI, which can be applicable here, following relations should also hold:

1. $WCm_C = WC_C, WCm_{NC} > WC_{NC}$, to give the penalty of not completing the committed task, as this occurred because the actions incompatible to the commitment must have occurred.

2. $WCm_{CR} \le WC_{CR}$, the negation for WCm_{CR} in equation (9) must be noted. It is to give penalty of not doing task within committed parameters, ultimately because of the reason that some actions incompatible to the commitment must have occurred.

3. Values of WCm_C, WCm_{CR}, WCm_{NC} can be taken under any fixed range, but for uniformity, we can take it between 0 and 1.

Now, in the case of calculation of CommI, the commitment for each task-type can be given same weight. So, the CommI of an agent can be defined as the simple arithmetic mean of the commitment indexes of agent for all task-types.

$$CommI = \frac{1}{n} * \sum_{i=1}^{n} CommI_i \quad \ldots(10)$$

The values corresponding to $N_C^k, N_{CR}^k, \quad N_{NC}^k$ and $ND_C^k, ND_{CR}^k, \quad ND_{NC}^k$ in the profiles are updated after taking the services of selected SPA.

2.2 Measuring Reputation of Agent

Using TI, SRA try to judge the trustworthiness of agent using various cognitive parameters. However, the trustworthiness of agent from the view of other similar SRAs is not judged by the TI. But it should be one of the important parameters for the selection of SPA. This is accomplished by the RI, which is the measure of reputation of agent. We have adapted the definition of reputation for information source presented in [1], for multi-agent based SWS composition system. Reputation is the amount of trust an SPA has created for itself through interactions with different SRAs. If an SPA consistently meets the expectations of SRAs, then it will increase its reputation, and likewise, not satisfying expectation of SRAs due to either incompetence or maliciousness will decrease its reputation. Checking reputation of agent also serves as social law mandating for the SPA to stay trustworthy to all SRAs. However, in calculation of TI, the SPA may publish unreliable information, if it is not controlled by any central body, but now, agent will risk the reputation it has been building among the SRAs. The agent with consistently low reputation can become isolated from the SRA community [1].

The reputation of an agent can be calculated using either of following mechanism:

1. A central controller is there, which has reputation indexes for all the published SPAs.
2. Each of the SRA maintains a separate Reputation Table (RT) in its service profile, which has reputation indexes of SPAs from its view.

The Reputation Table (RT) is a data structure which is maintained by the SRA and holds reputation indexes of all those SPAs from which the given SRA has taken services in past, for all those task-types for which services were taken. It must be noted that the reputation of an agent can be different for different task-types from the view of same SRA. An example structure for RT is shown in Figure 1. Each entry in the shown RT for requester agent R contains following elements:

i) The Service Provider Agent/Task-type identifier ($\langle P,T\rangle$).

ii) The reputation index from requester agent R for the provider agent P for task-type T ($RI_{R\to\langle P,T\rangle}$).

Now, the given SRA may not equally consider the reputation feedback from all the similar SRAs. The reputation feedback from some of the SRAs may be much affecting or reliable for the given SRA than the other ones.

$\langle P,T\rangle$	$RI_{R\to\langle P,T\rangle}$
$\langle p_2,T_1\rangle$	0.66
$\langle p_4,T_3\rangle$	0.76
$\langle p_2,T_4\rangle$	0.58
. . .	. . .
$\langle p_5,T_2\rangle$	0.87

Figure 1: A SRA's Reputation Table

So, the overall RI of SPA for the required task-type will be the weighted arithmetic mean of the reputation indexes for the required task-type from all the SRAs including the given SRA itself.

$$RI = \frac{\sum_{i=1}^{n} RI_i * WR_i}{\sum_{i=1}^{n} WR_i}, \quad Where \quad 0 \le RI_i \le 1 \qquad \ldots(11)$$

Where, RI_i is the reputation index from any service requester agent R_i for the concerned SPA for required task and WR_i is the reputation weight given by the SRA to the reputation feedback of R_i. One of definition for WR_i can be as follow:

$$WR_i = \begin{cases} =1 & If\ R_i\ is\ the\ given\ reference\ SRA \\ >0, \le 1 & If\ R_i\ is\ any\ other\ SRA \end{cases} \qquad \ldots(12)$$

The provision is also there to update the RI of selected SPA after taking its services by the given SRA in its local RT. So, if q is the quality rating given by the reference SRA to the reference SPA based on its services and RI' is the existing reputation index of this SPA in the RT of given SRA, then the updated RI can be calculated as:

$$RI = \varepsilon * RI' + (1-\varepsilon) * q\,,$$
$$Where \quad 0 \le \varepsilon \le 1, \quad 0 \le q \le 1 \qquad \ldots(13)$$

Where, ε is the relative weight given to the past reputation of SPA as compared to its present quality - rating.

This feedback system will not only cause dynamicity in the selection process of SPA, but will also affect its chances of selection in the future by any of the SRAs.

Hence, it will compel the SPA to consistently perform well to maintain its established reputation.

3. Experiment and Implementation

We have also implemented a semantic web service composition system which uses CPBSM for service selection. This system uses OWL [6] based service profiles developed using Jena [5]. The Jena based reasoning (Jena' OWLReasoner) and querying support which internally uses SPARQL [9] is also used. The negotiation and communication in the system can be maintained using FIPA Contract Net Protocol [10] and FIPA-ACL [4] respectively. Figure 2 shows result of selecting a SPA using CPBSM. Figure shows the result of applying the model to a semantic web composition system for education planning.

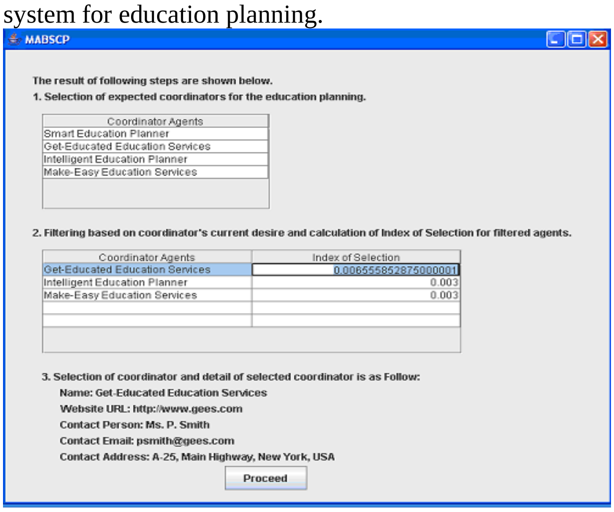

Figure 2: CPBSM based agent selection

Education planning is the problem of planning the complete process of taking the admission in some higher education program, which may involve various activities like counseling and preparation for entrance examination, choosing appropriate institute, getting funds, completing admission formalities, and arranging transportation to join. The selection of an agent which will coordinate all the activities in composition process has been done using CPBSM. Figure shows that 'Get-Educated Education Services (http://www.gees.com)', 'Make-Easy Education Services (http://www.make-easy.com)', 'Intelligent Education Planner (http://www.iep.com)' are the various discovered agents, which can perform coordinating activities for education planning. On each of these coordinator agents, the CPBSM is applied to calculate the IoS and the agent with maximum IoS i.e. 'Get-Educated Education Services (http://www.gees.com)' is selected as Coordinator agent.

4. Conclusion

The paper presents a novel selection model based on cognitive parameters like trustworthiness, reputation, capability, intention, commitment, desire etc. of services for selecting the best service among the available services for semantic web service composition process. A new formalization to cognitive parameters is presented and a novel architecture for measuring the reputation of a service provider is also presented. Categorizing the request into multiple task-types and considering this in selection process provides more reliable selection of service. The model is highly suited for selection in multi-agent based semantic web service composition process. An implementation of the proposed model by presenting a new area of application i.e. education planning is also presented. Our future work will involve further enhancing the presented model to increase its reliability and accuracy and to further explore the education planning as an application of semantic web.

References

[1] Barber, K.S., Kim, J., Belief Revision Process Based on Trust: Agents Evaluating Reputation of Information Sources, Lecture Notes in compute Science, Springer, V 2246, 2001.

[2] Cohen, P.R., Levesque, H.J., Intention Is Choice with Commitment, Artificial Intelligence, Elsevier, 42, p 213-261, 1990.

[3] Ermolayev, V., Keberle, N., Kononenko, O., Plaksin, S., Terziyan, V., Towards a Framework for agent-enabled semantic web service composition, Int. Jl. Of Web Services Research, v 1(3), p 63-87, 2004.

[4] FIPA Architecture Board, Foundation for Intelligent Physical Agents, FIPA Communicative Act Library Specification, http://www.fipa.org/specs/fipa00037/SC00037J.html, Web-Site accessed on Feb 12, 2008.

[5] HP Labs Semantic Web Programme, Jena- A Semantic Web Framework for Java, http://jena.sourceforge.net/, Website accessed March 01, 2008.

[6] McGuinness, D.L, Harmelen, F.V., OWL Web Ontology Language Overview, http://www.w3.org/TR/owl-features/, Website accessed on Feb 13, 2008.

[7] Padgham, L., Lambrix, P., Agent Capabilities: Extending BDI Theory, American Association for Artificial Intelligence, www.aaai.org, 2000.

[8] Pechoucek, M., Formal Representation for Multi-Agent Systems, Gerstner Laboratory, Czech Technical University in Prague,

http://agents.felk.cvut.cz/teaching/33ui2/bdi.pdf, 2003.
[9] Prudhommeaux, E., Seaborne, A., SPARQL Query Language for RDF, http://www.w3.org/TR/2008/REC-rdf-sparql-query-20080115/ , 2008.
[10] Smith, Davis, Foundation for Intelligent Physical Agents, FIPA Contract Net Interaction Protocol Specification, http://www.fipa.org/specs/fipa00029/SC00029H.html, Web-Site accessed on Feb 12, 2008.
[11] Tweedale, J., Ichalkaranje, N., Sioutis, C., Jarvis, B., Consoli, A., Phillips-Wren, G., Innovations in multi-agent systems, Journal of Network and Computer Applications, Elsevier, v 30(3), p 1089-1115, 2007.